Information fusion for real-time national air transportation system prognostics under uncertainty

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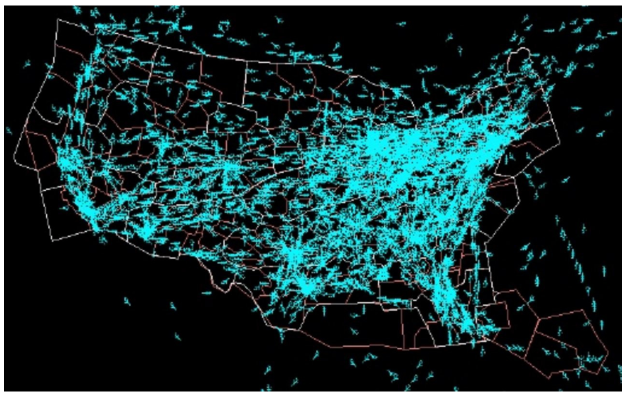
Outline

- Background and objectives
- Statement of work
    - Technical progress and achievements
    - Educational activities and achievements
- Project management
    - Project team
    - Research dissemination and broad impact
    - External advisory board
- Conclusions and future work

Background

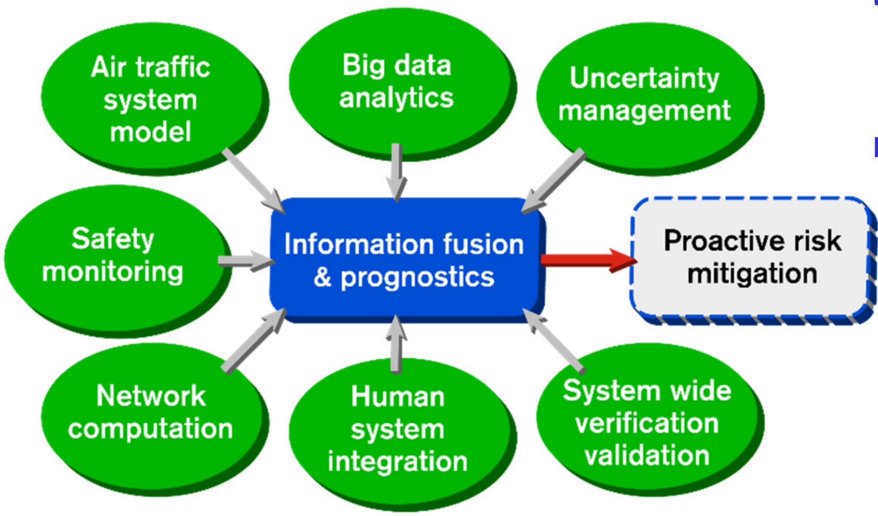


- NASA Aeronautics Research Mission Directorate (ARMD) vision for aeronautical research that encompasses a broad range of technologies to meet future needs of the aviation community
- Recent technology advances in sensors, networking, data mining, prognostics, and other analytic techniques enable proactive risk management for National Airspace System (NextGen)
- Technology convergence of multidisciplinary research to develop transformative concepts and to enable a safe and efficient aviation system
- Systematic training of next generation engineers and workforce pipeline for future aerospace industries and research

Objectives

- Real-time system-wide information fusion methodology for prognostics and safety assurance of the NAS
- Self-identified technical challenges (TC) and objectives
  - **TC 1:** Develop an extensible community-based NAS air traffic simulation system incorporating data-derived vehicle/subsystem level failure/fault models that can be used for system-wide safety assessment and integration with training simulations
  - **TC 2:** Determine information sources inventory associated with current ATM operations, model human ATM performance in simulator, and develop real-time sensors of human performance
  - **TC 3:** Determine faults and early damage indicators in the subsystems during ground and in-air fleetwide operations utilizing state of the art multiscale, multimodal sensors, data mining, feature extraction and classification
  - **TC 4:** Uncertainty quantification, verification and validation, and risk assessment tools for 80% increase in computational speed and 60% increase in confidence in risk assessment compared with existing approaches
  - **TC 5:** Integrated diagnostics, prognostics, probabilistic modeling, and simulation tools for 50% increase in accuracy compared with existing approaches

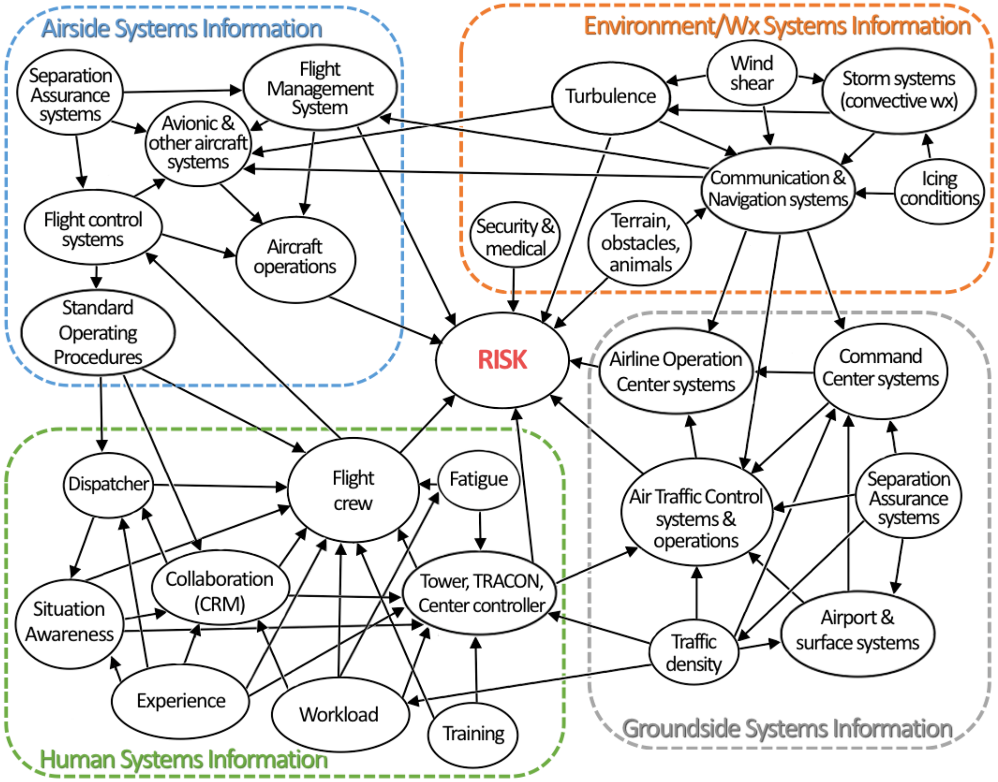
Proposed methodology and tasks



Schematic illustration of the proposed major research themes

- Highly multidisciplinary research themes are integrated together
- Seven major tasks:
  - Task 1. System-wide air traffic modeling and failure simulation
  - Task 2. Multi-modality safety monitoring, detection and data analysis
  - Task 3. Human system integration
  - Task 4. Uncertainty management and risk assessment
  - Task 5. Information fusion and prognostics
  - Task 6. Verification, validation, and safety assurance
  - Task 7. Integrated education, research, and demonstration

Information fusion – Bayesian Entropy Network (BEN) framework



- Integrate multiple types of information among multiple domains within the airspace system
- Bayesian Entropy Network (BEN) – based information fusion for Data, Experiences and Knowledge (DEK)

$$p(\theta) \propto \mu(\theta) \cdot \mu(x' \mid \theta) \cdot \boxed{e^{\beta \cdot g(\theta)}}$$

Entropy term for abstracted knowledge, physical constraints, and expert opinions

- Hybrid data-based and physics-based prognostics
- Assist the risk assessment and decision-making for safety assurance

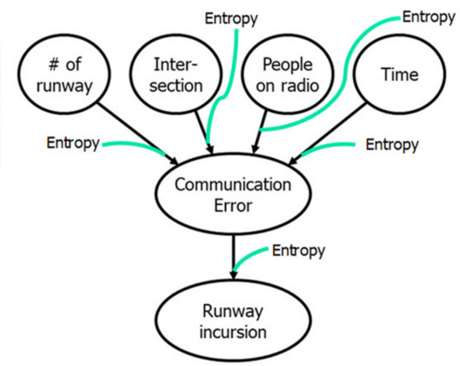
Information fusion – classification for runaway incursion

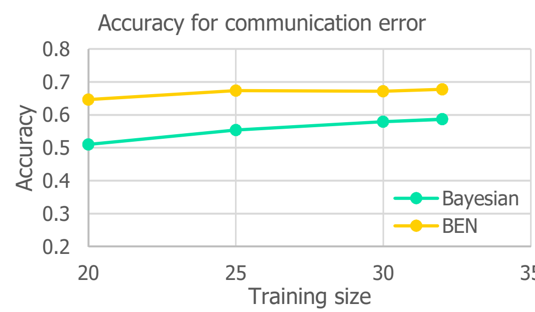
- Adding entropy information:
  - Expert linguistic information representing historical experiences

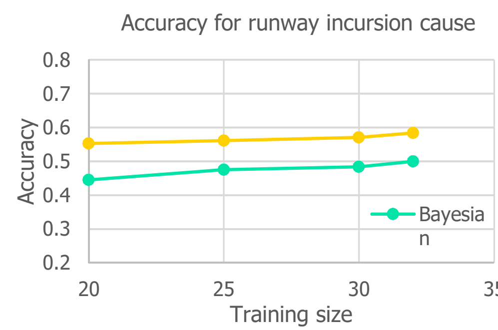
1. When the taxi clearance communication error is on the ATC side, the cause for runway incursion is more likely to be cross runway without clearance.
2. LUAW communication error can only lead to and is the only reason for attempt take-off without clearance

…..

  - Expressed as constraints on expected value of the posterior distribution

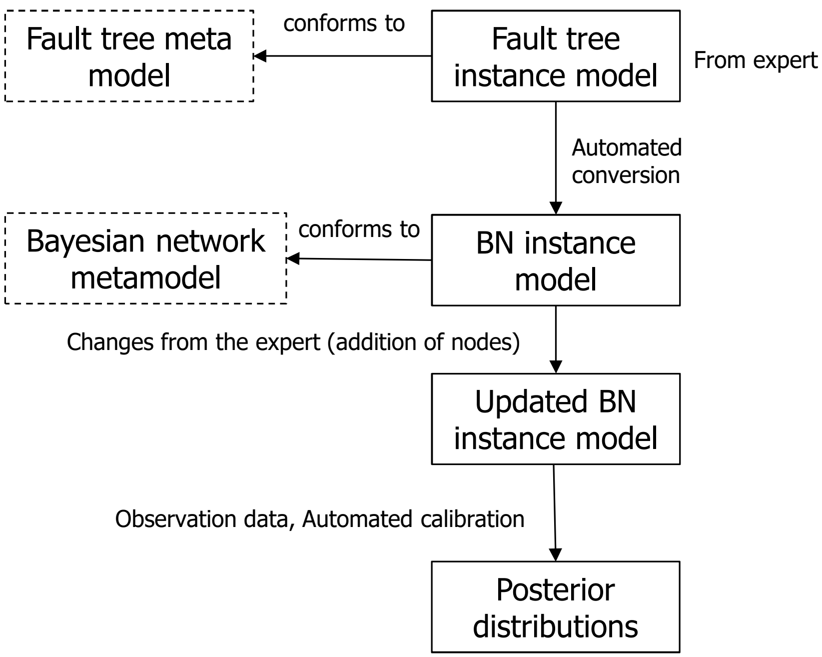


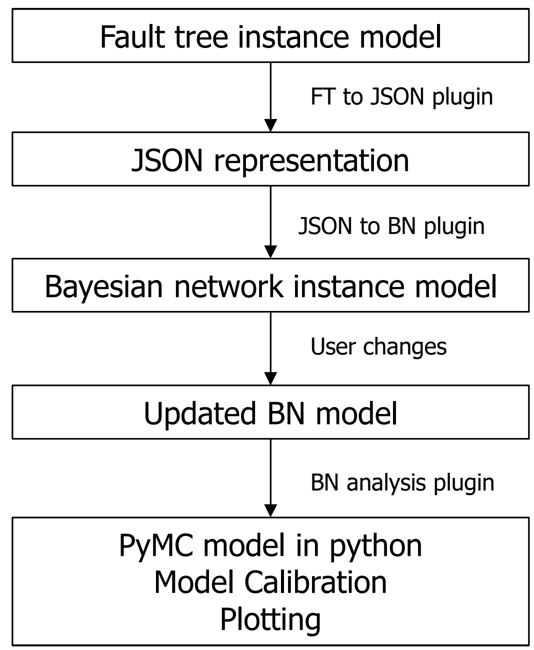




Information fusion – avoid mid-air collision

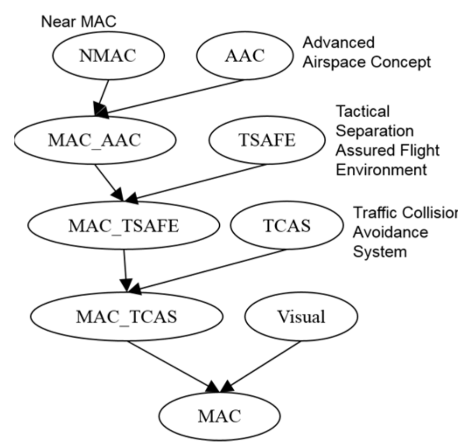
- Fuse machine learning models plus expert knowledge (fault trees)
- Convert existing system fault trees to Bayesian networks, instead of building from scratch
- Automate the conversion from fault tree to Bayesian network





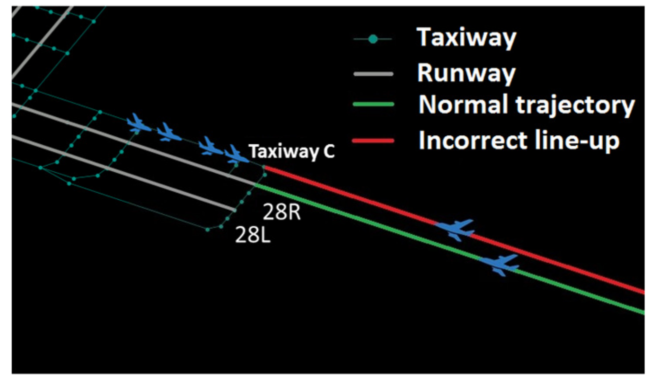
Nannapaneni & Mahadevan, AIAA Aviation 2018

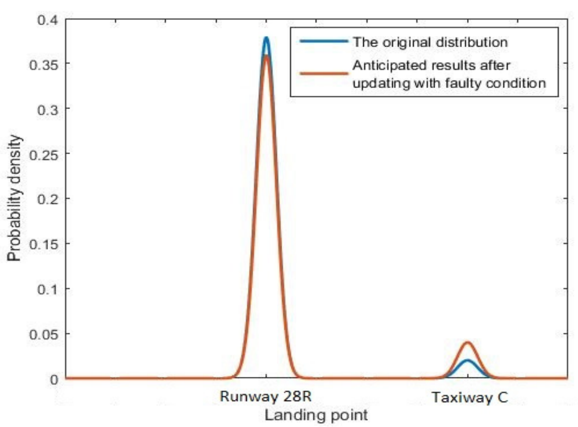
Aircraft self-separation example

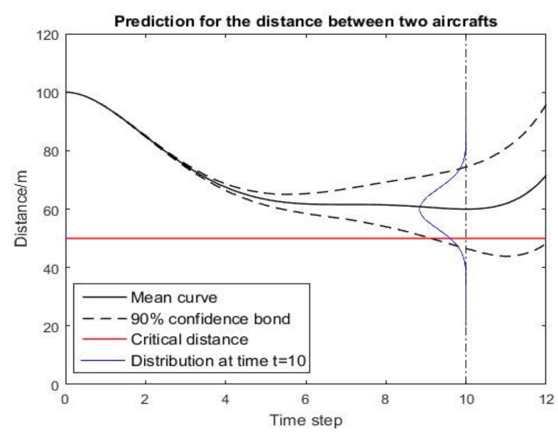


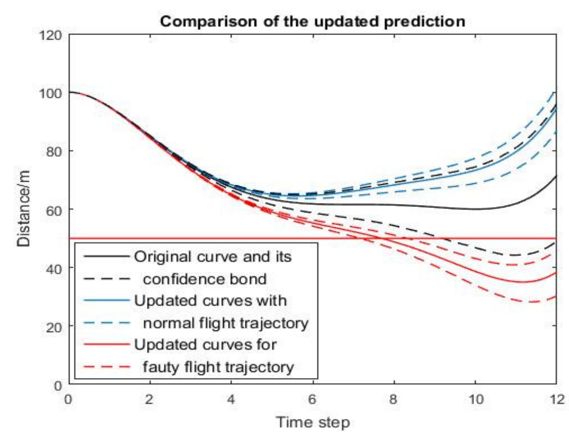
Information fusion – prognostics and safety metrics

- Simulating accidents for landing on taxiway using NATS
- Update the trajectory using ADS-B information and BEN
  - Predict the landing point at the airport and confidence level
  - Prognostics for potential collision of any pair near terminal region



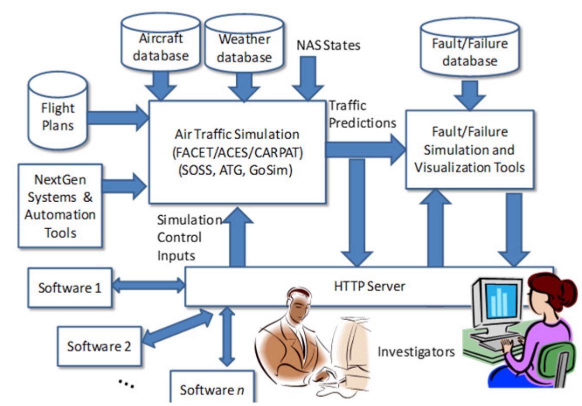






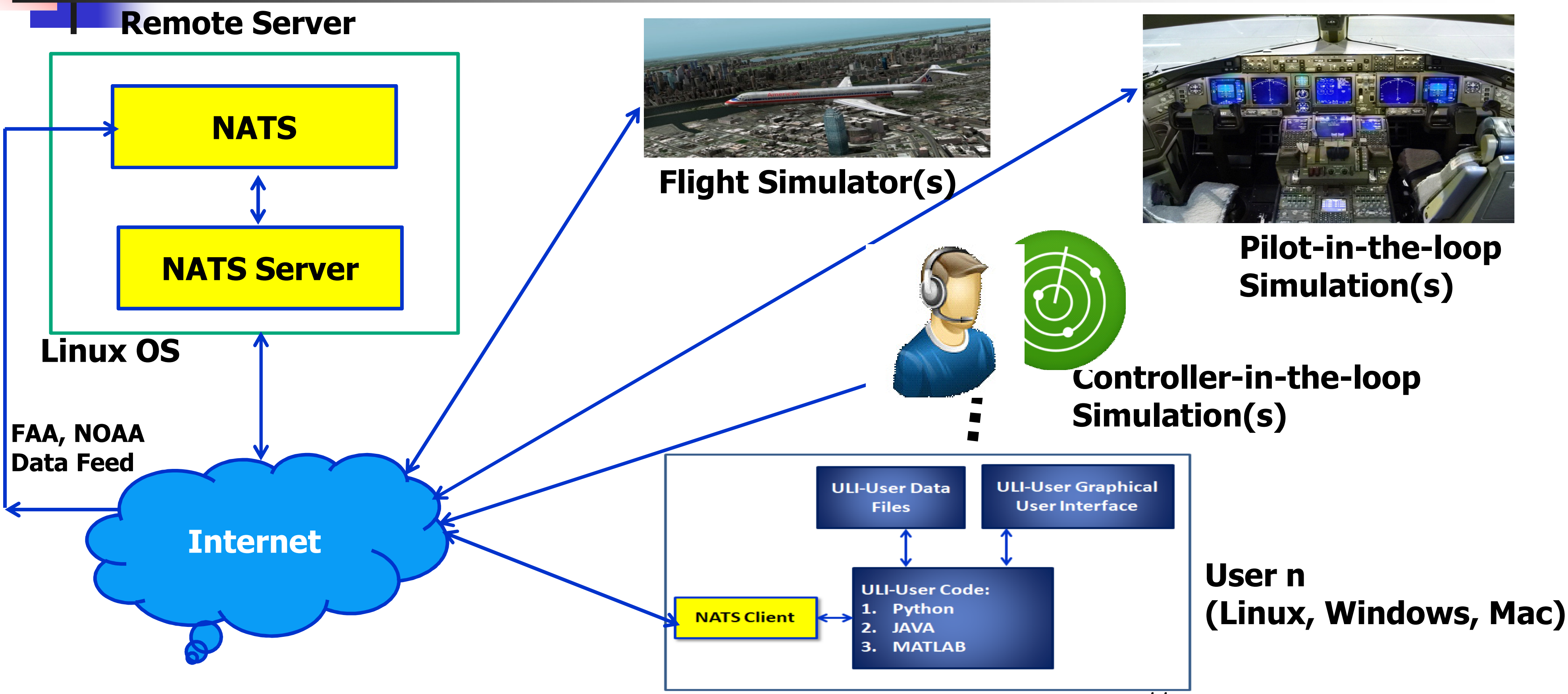
Air traffic simulation – NATS

- Community-based software for formulating and analyzing NAS safety prognostics problems under realistic NAS traffic environments.
  - National Airspace Traffic Safety-Analysis (***NATS***) Server-Client Software released (Python, MATLAB, Java interfaces)
    - 55 Airports in the NAS with all the gates, taxiways, runways, approach, go-around, and departure procedures
    - Terrain Profile for the Contiguous United States
    - NOAA wind and convective weather
  - Multiple application examples and software demos
  - Interface with any user-defined real-time simulation
  - Human Pilot/Controller error models
- 2018 PHM Conference paper summarizing the software status

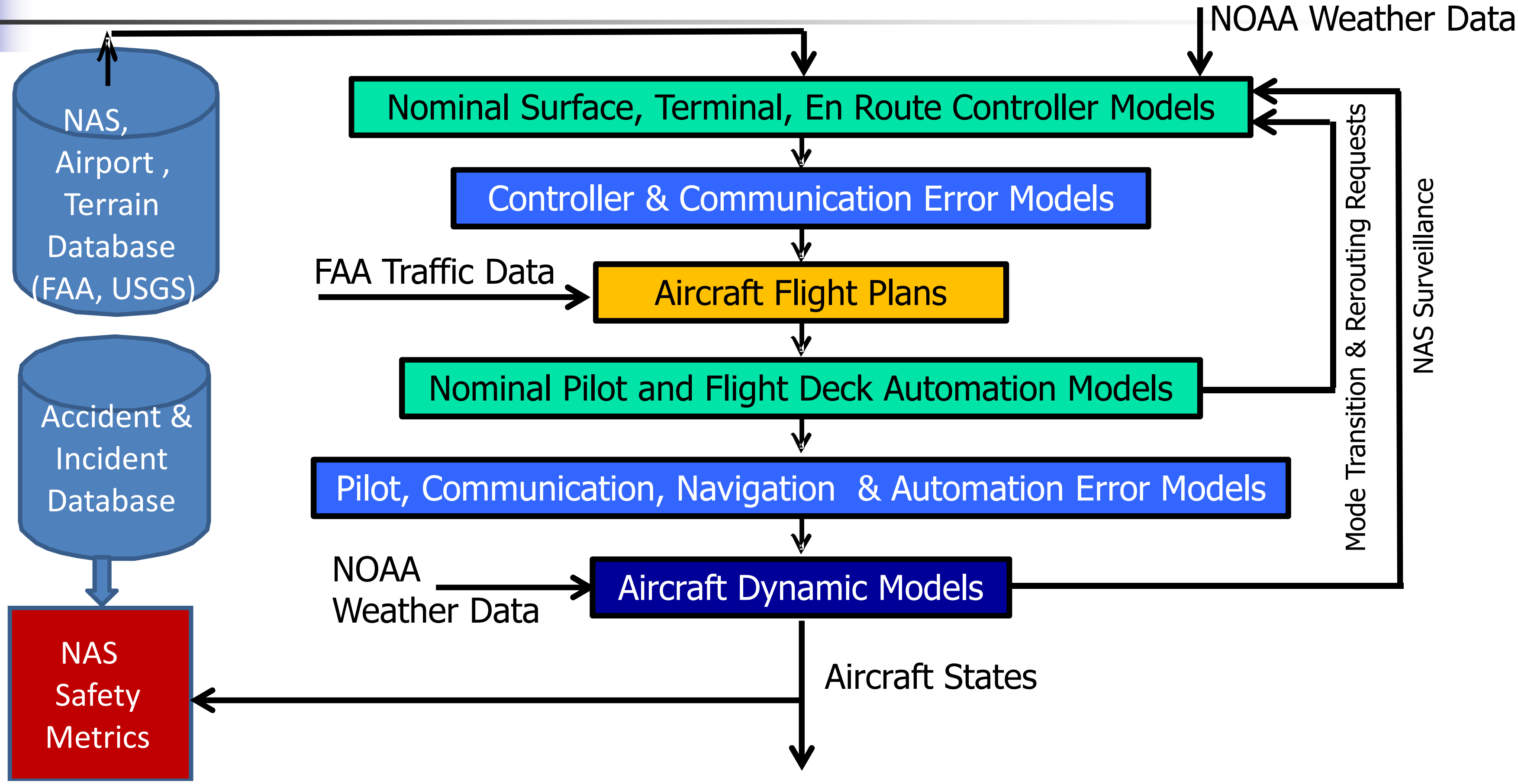


Schematic Illustration of NAS Air Traffic Prediction and fault/Failure Simulation

Air traffic simulation – real-time cloud-based computing

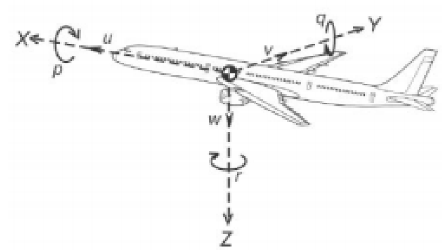


Air traffic simulation – information flow



Air traffic simulation – hybrid learning for aircraft dynamics

Physics
(State-space model)

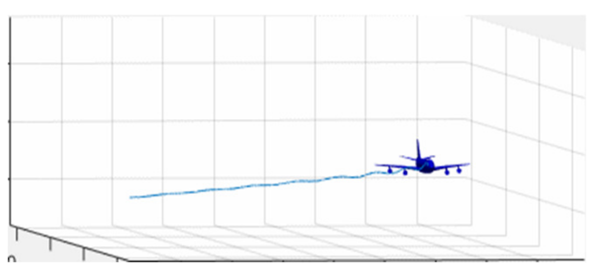


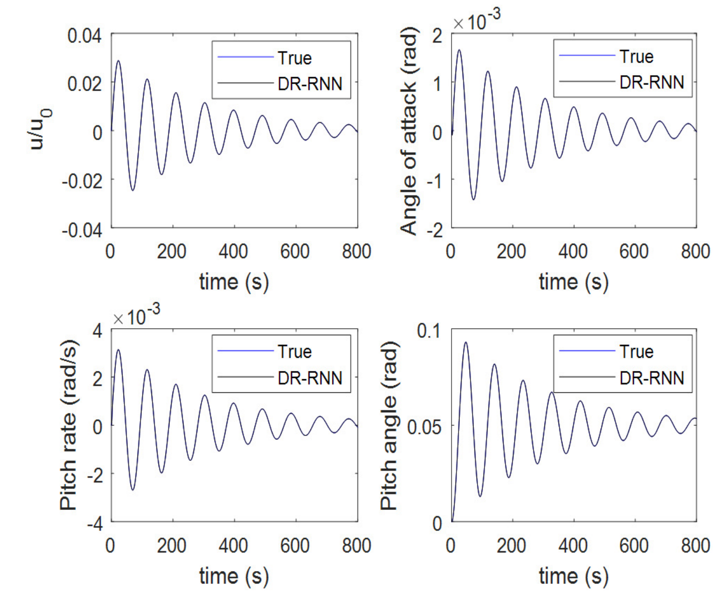
Deep Residual RNN
(DR-RNN)

$$\boldsymbol{q}_{t+1}^{(k)} = \boldsymbol{q}_{t+1}^{(k-1)} - \boldsymbol{W} \circ \tanh(\boldsymbol{U}\boldsymbol{r}_{t+1}^{(k)}), \text{ for } k = 1$$

$$\boldsymbol{q}_{t+1}^{(k)} = \boldsymbol{q}_{t+1}^{(k-1)} - \frac{\eta_k}{\sqrt{G_k + \varepsilon}} \boldsymbol{r}_{t+1}^{(k)}, \text{ for } k > 1$$

Physics-based Learning
(using 2-layer DR-RNN)

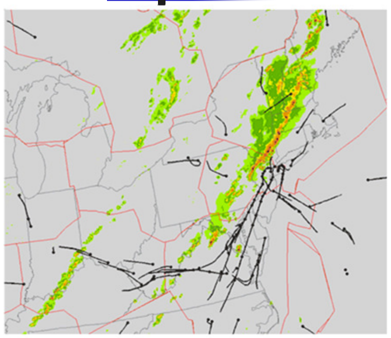


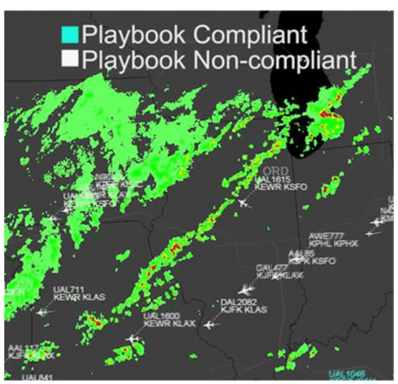


	DR-RNN (step size = 0.1 s)	RK (step size = 0.002 s)	RK (step size = 0.005 s)
Computation time (s)	7.4	605.4	241.1
Average prediction error	2.60e-4	3.78e-4	5.72e-4

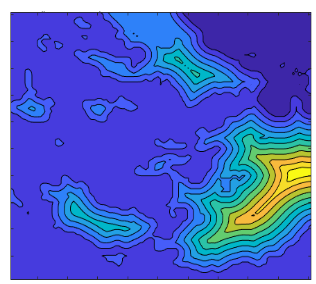
Air traffic simulation – automatic weather avoidance

- Objectives:
  - Develop an automated trajectory prediction algorithm for arbitrary weather cell shapes at the pixel level
  - Include weather dynamics and forecasting uncertainties for planning
  - Combine simple geometric models and CNN-based learning to understand the decision making of pilot and controller

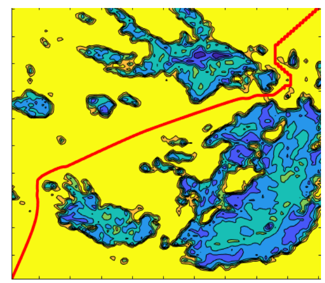




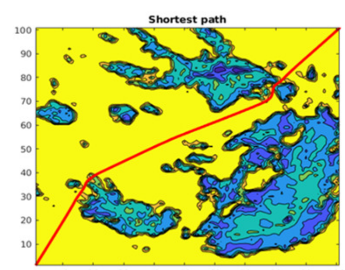
Raw weather image



Fast Marching Map

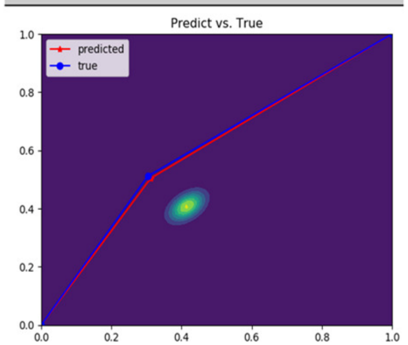


Probabilistic decision 1



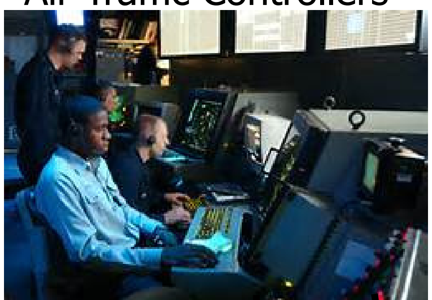
Probabilistic decision 2

Network Configuration	
Layer number	Layer Type
1	3x3-Conv-32
2	3x3-Conv-32
3	2x2-maxpool
4	3x3-conv-64
5	3x3-conv-64
6	2x2-maxpool
7	3x3-conv-128
8	3x3-conv-128
9	2x2-maxpool
10	512-fc
11	64-fc
12	2-sigmoid



Human system integration– human factors and operational error

Air Traffic Controllers



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Operational Errors

Scorecard

Safe & Effective NAS

Situation awareness

Cognitive Workload

Fatigue…

Density

Weather

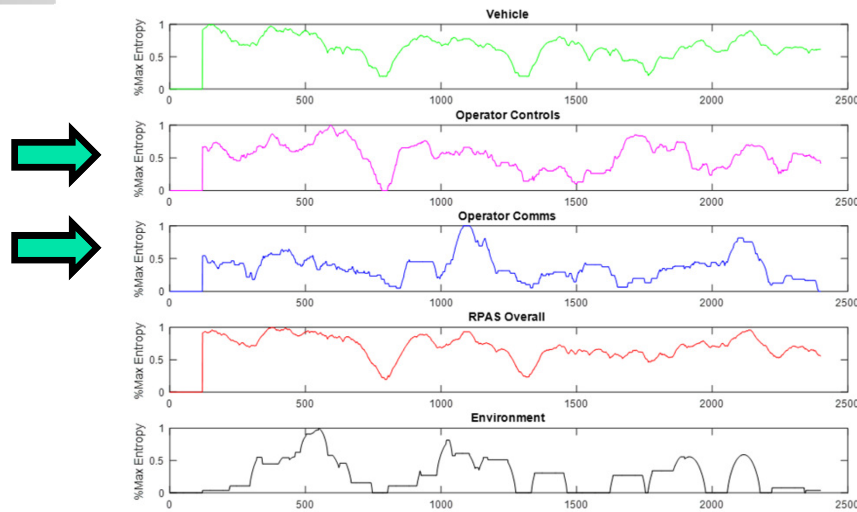
Separation…

Real Time Communication Data as a Surrogate (voice and data communications)

- How do human factors (e.g., SA, cognitive load) of ATCs interact with factors in the NAS to affect ATC performance (operational errors) and a safe and effective NAS?
- Need access to real-time data that provides information on problematic human states that may lead to operational error→ Communication data

Human system integration – hypotheses for testing

- *Communications data can serve as a sensor for the human part of the NAS*
- *Changes in the ATC-pilot state may correspond to changes in communication patterns which can signal potential operational errors/risk*



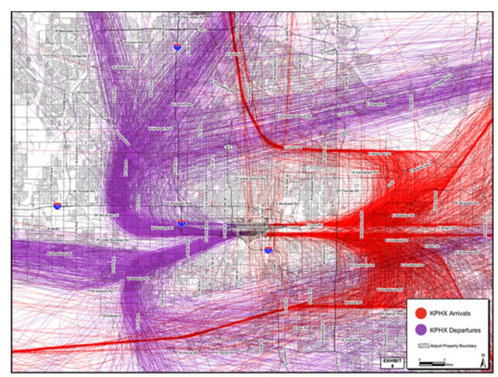
Notional diagram depicting patterns of communication changing over time with other parts of the system

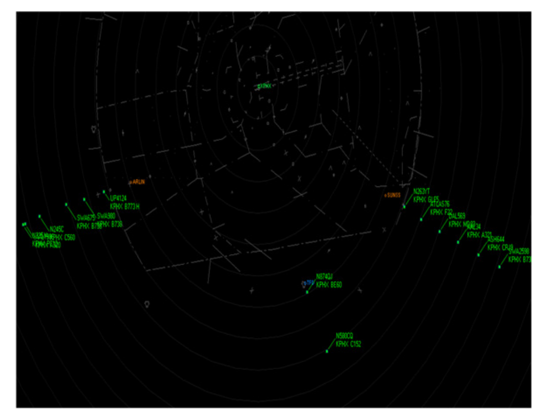
We are addressing this hypothesis through:

- Literature Review
- Existing ATC voice comms
- SWIM data
- Simulation (in which we can push the boundaries of ATC performance)

Human system integration – design of ATC experiment

- 12 Experienced (retired) and inexperienced (students) ATCs
- Up to 4 pseudo pilots (students) each controlling 4-8 planes
- Simulated approach scenarios
- Baseline normal conditions and increasing traffic density
  - Traffic density – 4-32 planes per sector
  - Complicating events
    - Separation issues
    - Loss of engine
    - Pilot miscommunication
    - Measures
- ATC Operational Error – breach of separation limits
- Measures
  - Voice Communication (patterns over time – detect change)
    - Volume – how much communication over time
    - Flow – who talks to whom patterns
    - Voice – pitch, volume changes over time
  - Facial Expression – cameras and affective software labeling
  - Eye blink rate (Pingbo Tang)
  - Keystrokes/Data comm





Human system integration – VORATS

- Voice Recognition for Air Traffic Simulators (VORATS)
  - Simulator independent
  - Automatic recording and translating, self-triggering
  - IoT with distributed computation
  - Easily expandable (N x Pi)
  - Automatic recognize the people (with Pi ID)
  - Data with time stamp for integration
- Fulton Undergraduate Research Initiative (FURI) project (pending)
- Integrated research and student education

Data analytics – text mining for safety reports

Problem Definition: Using 2246 accident Reports from NTSB (Part 121) to accomplish two tasks:

1. Task 1: Classify the states in which the accident happened
2. Task 2: Classify the actual causes which led to the accident

Experiment Process:
4 machine learning algorithms: Linear SVM, Non-linear SVM, Multinomial Naïve Bayes (MNB), Gradient Boosting Decision Tree (GBDT).

Conclusion: Linear SVM and GBDT are the optimal models for our tasks, in terms of the tradeoff among accuracy, efficiency, and explanation capabilities.

Task 1: Classify the **states** in which the accident happened

Table 1. Classification accuracy using linear SVM in **Task 1**

	C = 0.01		C = 0.1		C = 1		C = 10		C = 100		C = 1000	
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
Training accuracy	0.552	0.014	0.783	0.012	0.989	0.002	1.000	0	1.000	0	1.000	0
Validation accuracy	0.496	0.027	0.587	0.035	0.632	0.030	0.607	0.024	0.598	0.023	0.599	0.021
Testing accuracy	0.277	0.014	0.273	0.029	0.445	0.057	0.450	0.043	0.441	0.046	0.441	0.046

Table 2. Classification accuracy using non-linear SVM in **Task 1**

	$C = 10^2$		$C = 10^3$		$C = 10^4$		$C = 10^5$		$C = 10^6$		$C = 10^7$	
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
Training accuracy	0.244	0.020	0.635	0.013	0.993	0.002	1.000	0	1.000	0	1.000	0
Validation accuracy	0.212	0.038	0.517	0.023	0.623	0.027	0.620	0.024	0.620	0.024	0.620	0.024
Testing accuracy	0.186	0.101	0.273	0.000	0.432	0.055	0.436	0.055	0.436	0.055	0.436	0.055

Table 3. Classification accuracy using Multinomial Naïve Bayes in **Task 1**

	$\alpha = 0.001$		$\alpha = 0.01$		$\alpha = 0.1$		$\alpha = 1$		$\alpha = 10$	
	mean	std	mean	std	mean	std	mean	std	mean	std
Training accuracy	0.921	0.006	0.895	0.005	0.769	0.102	0.546	0.016	0.423	0.035
Validation accuracy	0.501	0.028	0.515	0.036	0.501	0.035	0.452	0.029	0.365	0.045
Testing accuracy	0.227	0.020	0.245	0.030	0.223	0.014	0.277	0.014	0.277	0.014

Table 4. Classification accuracy using GBDT in **Task 1**

	$\eta = 0.0001$		$\eta = 0.001$		$\eta = 0.01$		$\eta = 0.1$		$\eta = 1$	
	mean	std	mean	std	mean	std	mean	std	mean	std
Training accuracy	0.499	0.028	0.710	0.010	0.819	0.006	1.000	0.001	1.000	0.001
Validation accuracy	0.440	0.042	0.589	0.028	0.639	0.029	0.659	0.024	0.536	0.049
Testing accuracy	0.250	0.037	0.464	0.057	0.473	0.030	0.536	0.049	0.423	0.100

Task 2: Classify the **actual causes** which led to the accident

Table 5. Classification accuracy using linear SVM in **Task 2**

	C = 0.01		C = 0.1		C = 1		C = 10		C = 100		C = 1000	
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
Aircraft issues	0.427	0.058	0.450	0.065	0.681	0.049	0.708	0.039	0.708	0.035	0.706	0.034
Personnel issues	0.190	0.151	0.291	0.091	0.412	0.112	0.451	0.130	0.456	0.131	0.451	0.126
Environmental issues	0.326	0.092	0.563	0.115	0.581	0.118	0.558	0.090	0.544	0.090	0.544	0.090

Table 6. Classification accuracy using non-linear SVM in **Task 2**

	$C = 10^2$		$C = 10^3$		$C = 10^4$		$C = 10^5$		$C = 10^6$		$C = 10^7$	
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
Aircraft issues	0.429	0.059	0.514	0.052	0.707	0.038	0.704	0.035	0.704	0.035	0.704	0.035
Personnel issues	0.085	0.134	0.337	0.086	0.456	0.119	0.456	0.119	0.456	0.119	0.456	0.119
Environmental issues	0.324	0.092	0.579	0.118	0.546	0.099	0.546	0.088	0.546	0.088	0.546	0.088

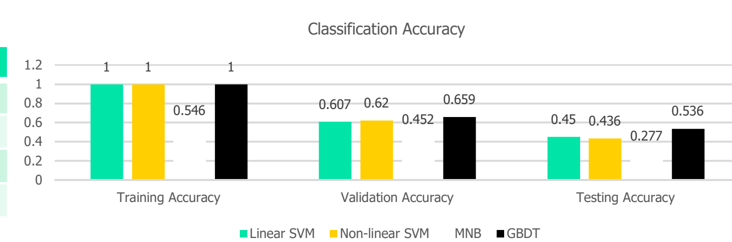
Table 7. Classification accuracy using Multinomial Naïve Bayes in **Task 2**

	$\alpha = 0.001$		$\alpha = 0.01$		$\alpha = 0.1$		$\alpha = 1$		$\alpha = 10$	
	mean	std	mean	std	mean	std	mean	std	mean	std
Aircraft issues	0.596	0.057	0.605	0.044	0.502	0.063	0.439	0.053	0.443	0.051
Personnel issues	0.397	0.083	0.417	0.098	0.417	0.053	0.312	0.070	0.225	0.152
Environmental issues	0.536	0.107	0.526	0.116	0.524	0.101	0.365	0.085	0.326	0.091

Table 8. Classification accuracy using GBDT in **Task 2**

	$\eta = 0.001$		$\eta = 0.01$		$\eta = 0.1$		$\eta = 1$		$\eta = 10$	
	mean	std	mean	std	mean	std	mean	std	mean	std
Aircraft issues	0.316	0.162	0.527	0.029	0.648	0.046	0.583	0.049	0.000	0.000
Personnel issues	0.292	0.075	0.492	0.091	0.532	0.104	0.487	0.115	0.195	0.145
Environmental issues	0.326	0.091	0.648	0.121	0.654	0.136	0.625	0.100	0.089	0.131

	Validation Accuracy	Training Efficiency	Explanation
Linear SVM	**0.632**	**Efficient**	**Easy**
Non-linear SVM	0.623	Efficient	Hard
MNB	0.515	Efficient	Hard
GBDT	0.659	Time-consuming	Easy

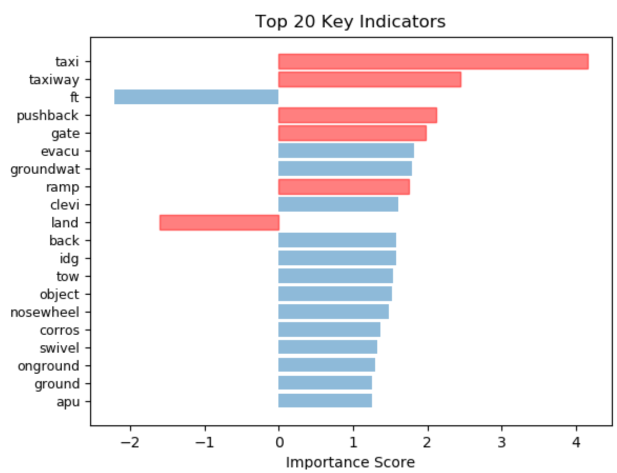


Data analytics – automatic safety indicator extraction

- **Task 1:** The indicators whose bars are marked red are *taxi*, *taxiway*, *pushback*, *gate*, *ramp* and *land*, which are intuitively relevant to our classification task.

- **Task 2 (aircraft issue as an example):** Similarly, the keywords with red bars are relevant words to this issue. Examples include *gear*, *nut*, *trunnion*, *land*, *tire*, *march*, *carcass*, *touchdown* and *overhaul*, which are intuitively relevant key indicators to identify Aircraft issues for accident reports.

Accident state indicators



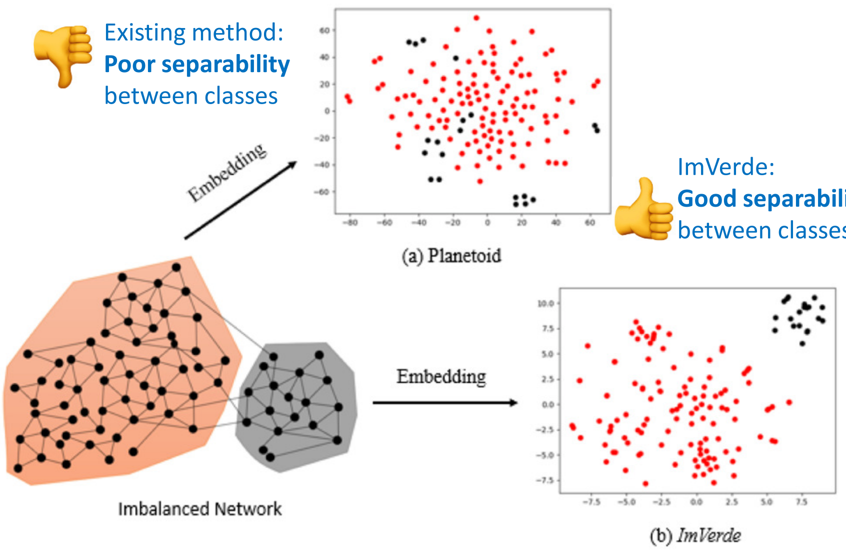
Aircraft issue indicators

Conclusion: Our machine learning models match our intuition by using highly relevant features instead of using the metadata from the reports in the database.

Data analytics – imbalanced data of NAS safety reports

A Novel Model for Learning Representations from Imbalanced Data

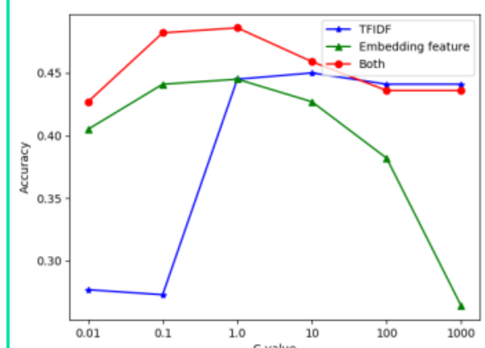
- A novel random walk model named Vertex-Diminished Random Walk
- It encourages the random particle to walk within the same class, leading to more accurate node-context pairs
- Semi-supervised method for learning representations from both label information and graph structure



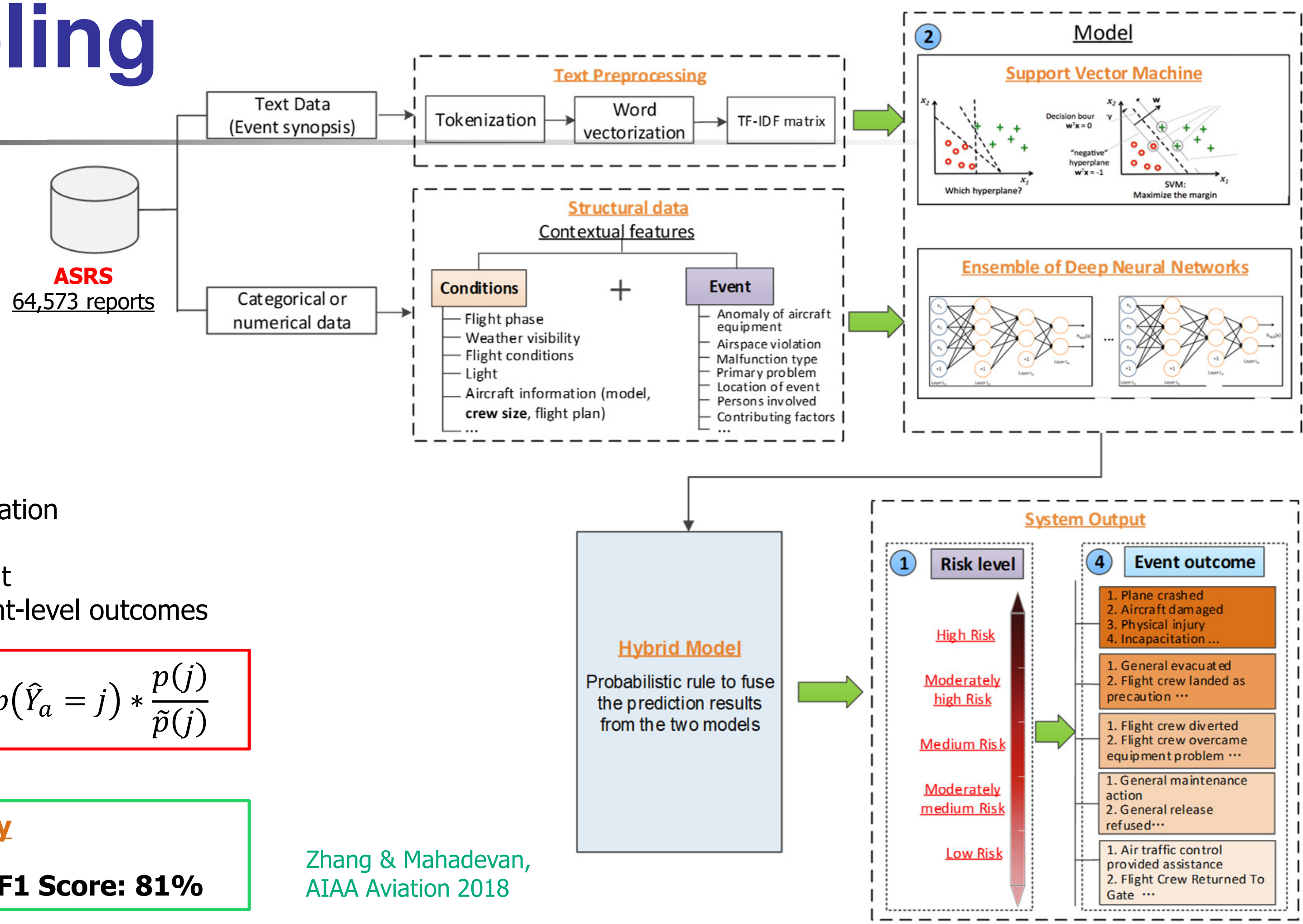
Preliminary Results on NTSB Data Set

Methods	Recall@k
DEEPWALK	0.500
Node2vec	0.467
GraRep	0.516
Planetoid	0.472
ImVerde-r	0.522
ImVerde-e	0.500
ImVerde-a	0.538

Furthermore, we compared the new embedding features with the original TF-IDF features. As shown below, the concatenation of embedding and TF-IDF features improves the classification performance with linear SVM. And a smaller parameter C is preferred for the embedding features compared to TF-IDF features alone.



Data analytics – hybrid model assembling



Data Sources

1. Aviation Safety Reporting System (ASRS)
2. System-wide Information Management (SWIM) data
3. National Transportation Safety Board (NTSB) accident analysis reports

Four-step Framework

1. Risk-based event outcome categorization
2. Hybrid model construction
3. Probabilistic fusion rule development
4. Map the risk-level prediction to event-level outcomes

$$p(Y_a = i) = \sum_{j=1}^{5} p(\boldsymbol{Y} = \boldsymbol{i} | \widehat{\boldsymbol{Y}} = \boldsymbol{j}) p(\hat{Y}_a = j) * \frac{p(j)}{\tilde{p}(j)}$$

↓

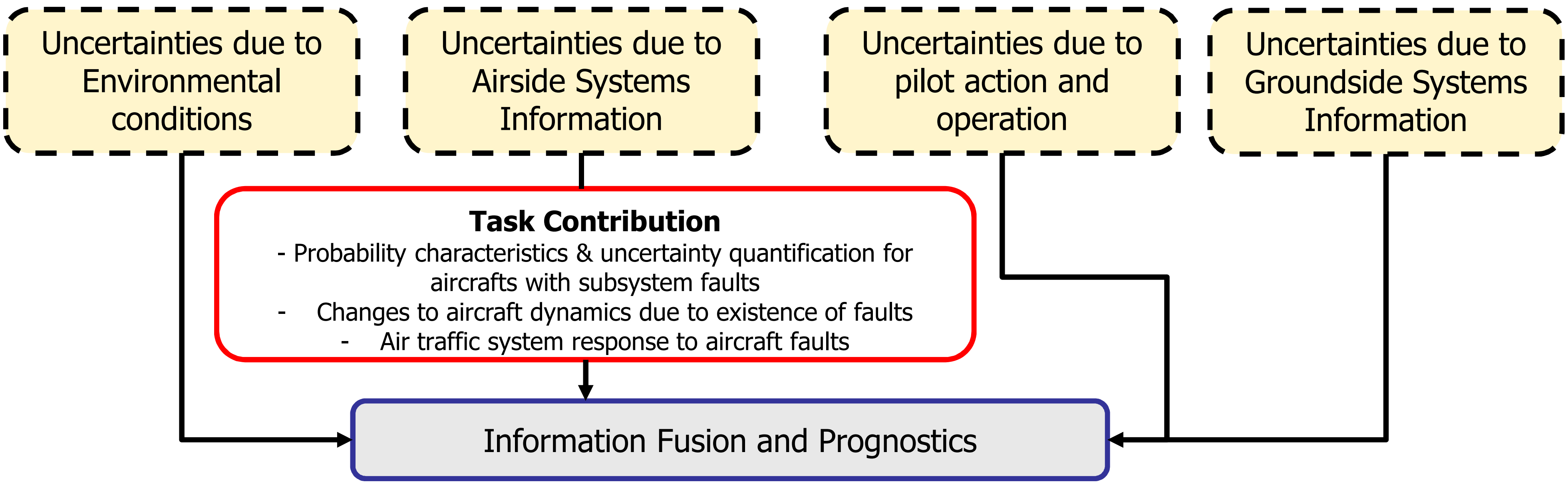
Prediction Accuracy

Precision: 81% Recall: 81% F1 Score: 81%

Zhang & Mahadevan, AIAA Aviation 2018

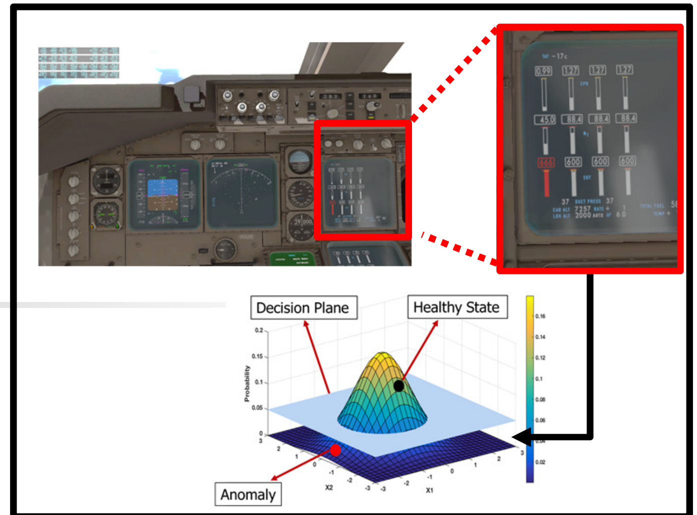
Monitoring and sensing – big picture of airside monitoring

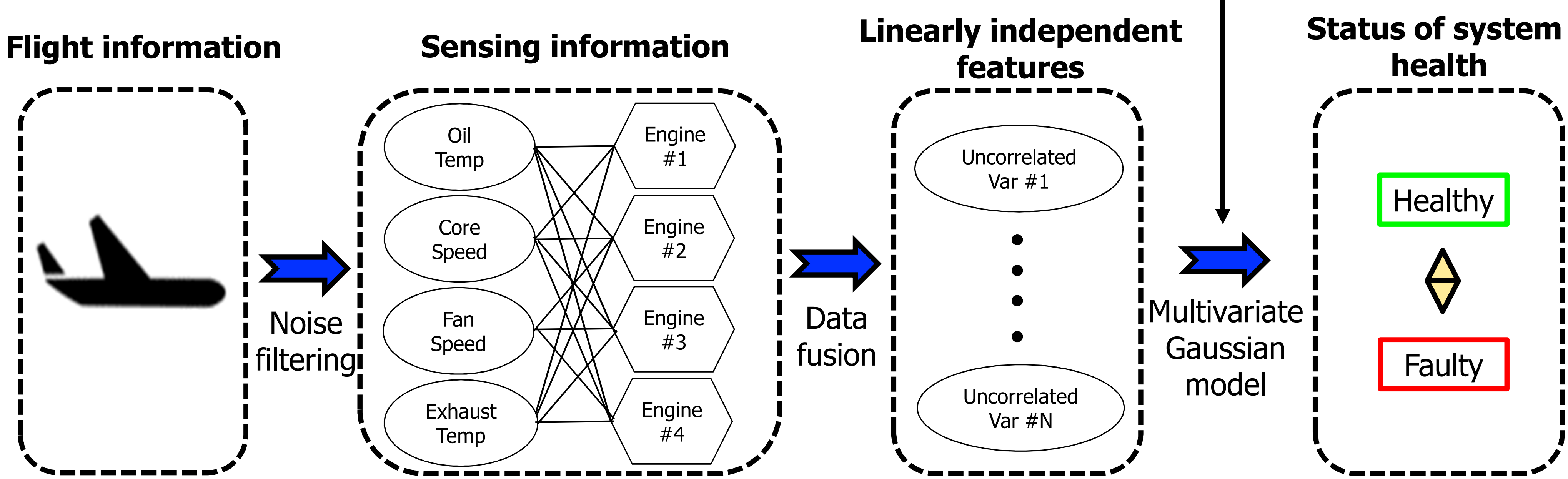
- Dimensional reduction – Autoencoder
- Feature extraction for handling critical system parameters
- Anomaly detection in real airline dataset & simulated flight dataset



Monitoring and sensing - anomaly detection

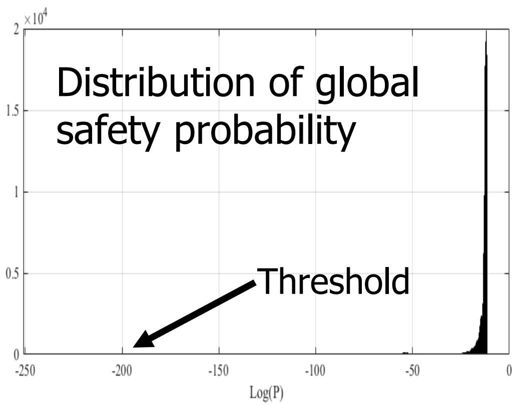
- Current model tested with a reduced dataset in cruise phase for online monitoring using simulated fault cases



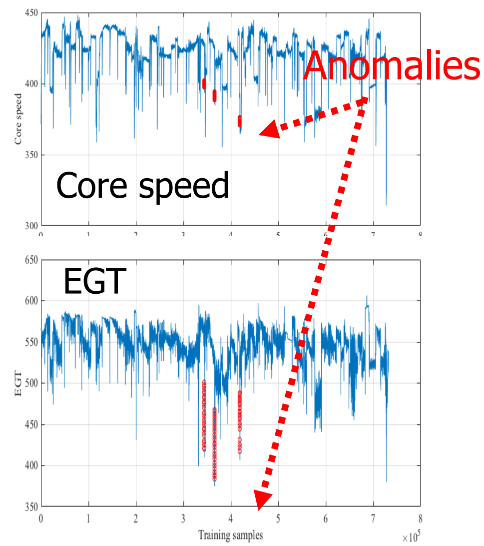


Monitoring and sensing – indication of pilot behavior

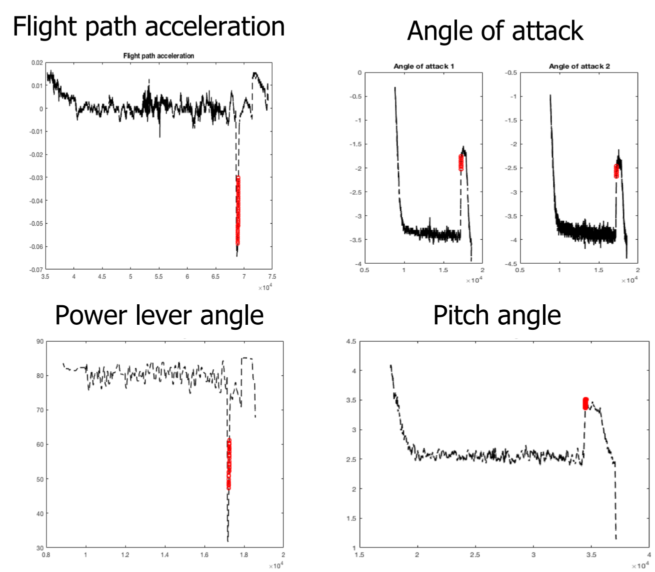
- 458 flight data investigated
- Distribution of global safety probability constructed in logscale (threshold set to be -200)
- Anomalies in aircraft detected in 3/458 flights



Anomaly in sensing signal

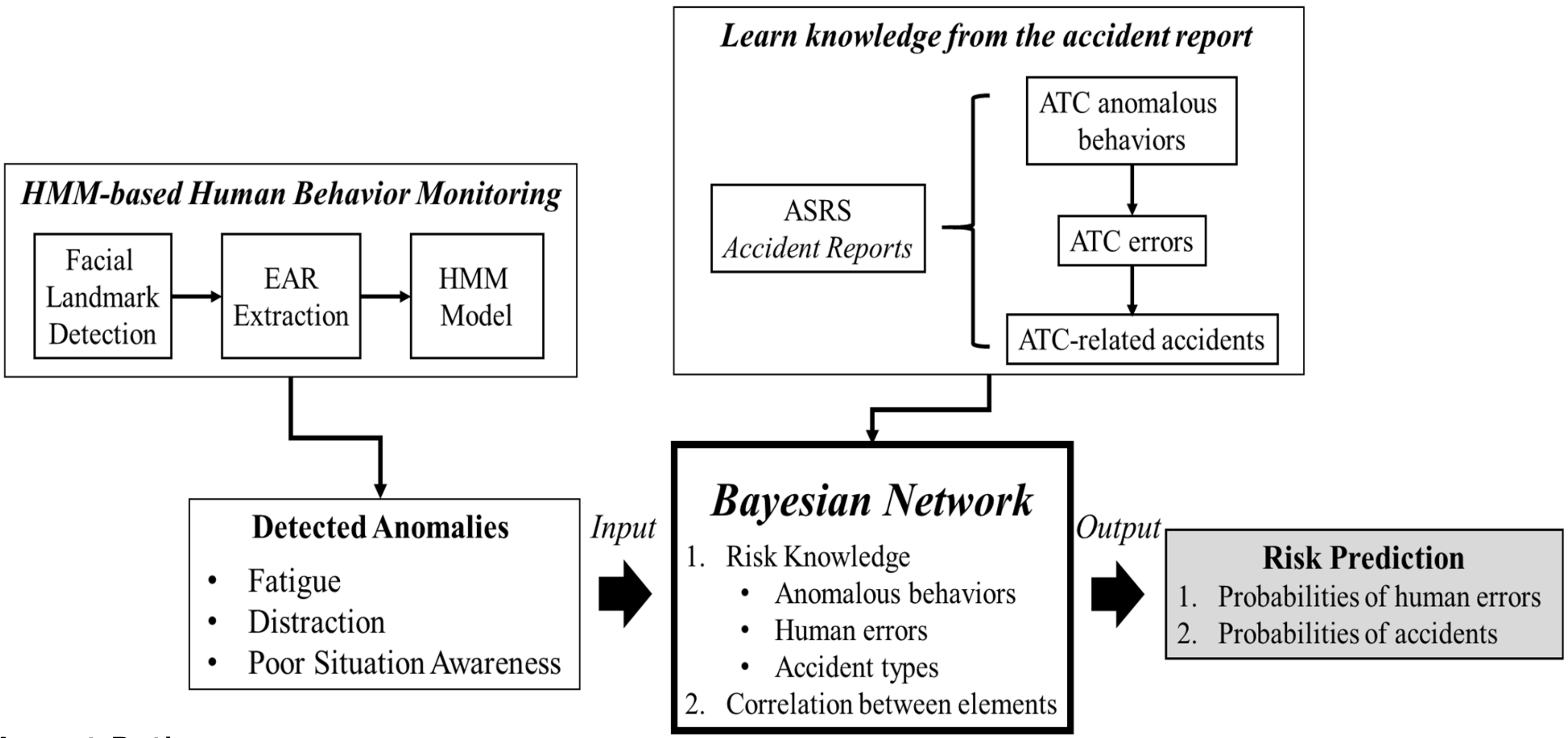


Aircraft response



- Identical aircraft dynamics in three detected anomaly cases
- Drop in path longitudinal acceleration; increases in angle of attack & patch angle
- Pilot reduces power lever angle

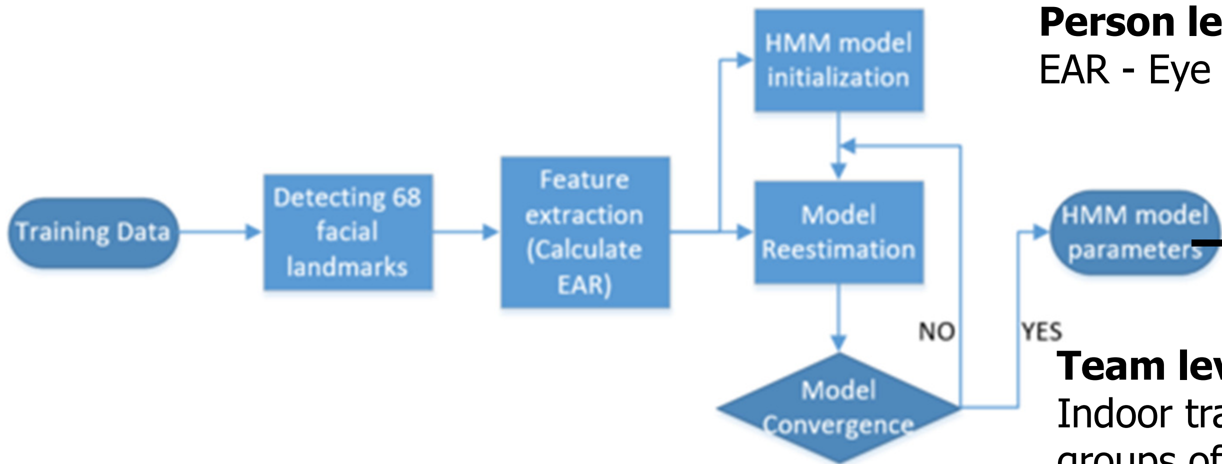
Monitoring and sensing – human behavior monitoring



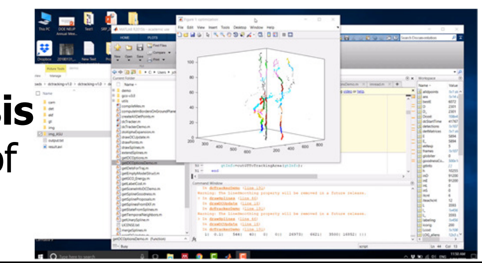
*EAR - Eye Aspect Ratio

Monitoring and sensing – computer vision technique

ATC/HUMAN SENSORS



Person level analysis
EAR - Eye Aspect Ratio

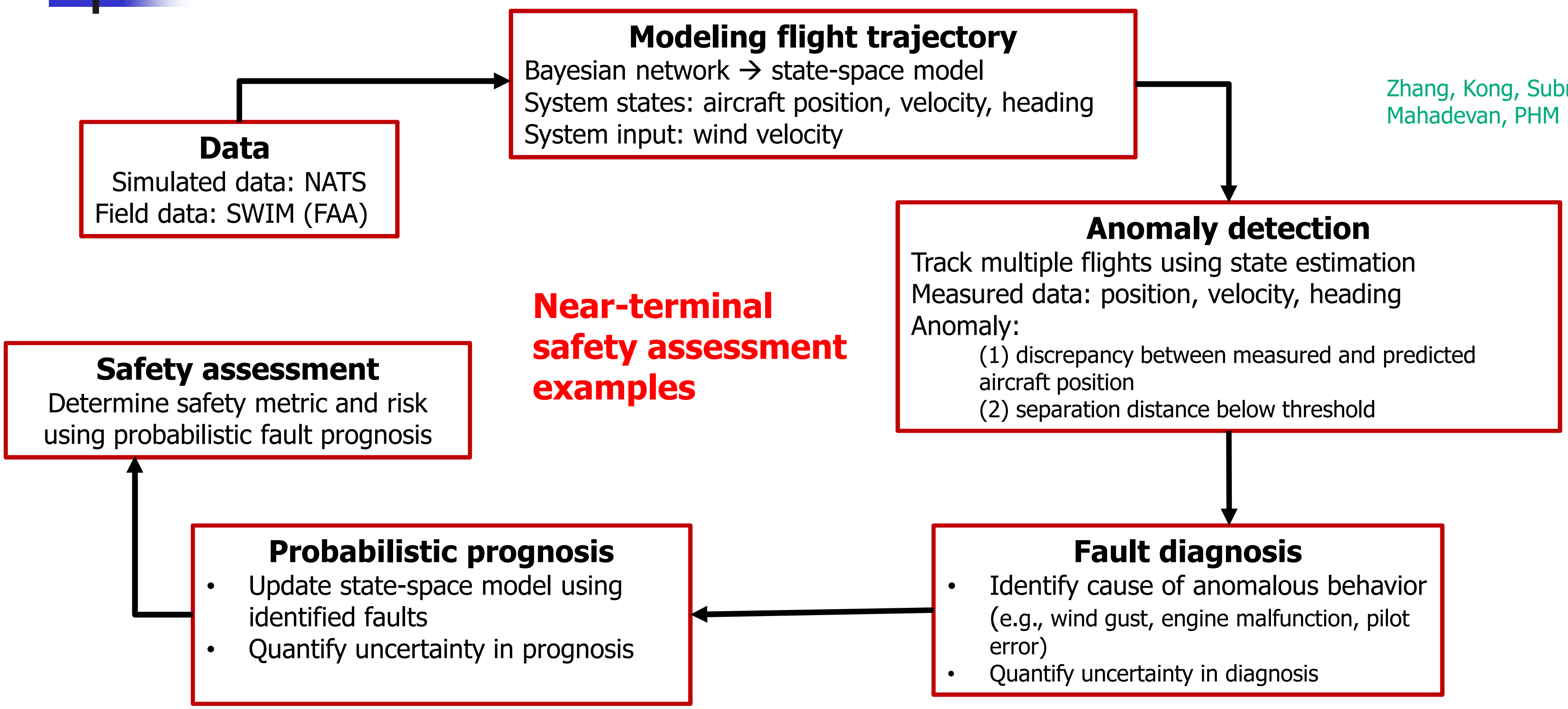


Team level analysis
Indoor trajectories of groups of people

Outdoor Site level analysis
Groups of people across job site for collaboration analysis

Uncertainty management – uncertainty in diagnostics and prognostics

Zhang, Kong, Subramanian, Mahadevan, PHM 2018



Uncertainty management – an illustration example

ATL Air Traffic in BlueSky

In-conflict aircraft (orange) undergo conflict detection and resolution (CD&R) based their state-space diagrams to avoid LoS.

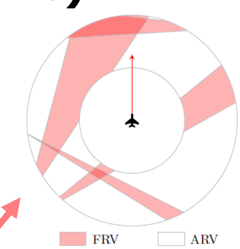
SWIM Flight Plans to BlueSky Scenario

```
0:02:09.04>CRE          DAL2396     B752      33.019
0:02:09.04>DAL2396      ORIG        KRSW
0:02:09.04>DAL2396      DEST        KATL      RW27L
0:02:09.03>CRE          DAL369      A320      33.207
0:02:09.03>DAL369       ORIG        KATL      RW27R
0:02:09.03>DAL369       DEST        MNMG
0:02:16.14>ENY3758      HDG         177.965
0:02:16.14>ENY3758      ALT         32000.0
0:02:16.14>ENY3758      SPD         395.0
```

- Create aircraft by ID, type, position, and speed
- Assign origin, destination and runway (for ATL)
- Per SWIM modify HDG, ALT, SPD

State-Space Diagrams (SSDs)

The state-space diagram is the intersection of forbidden and reachable velocities and defines the set of *Forbidden* and *Allowable* Reachable Velocities (FRVs and ARVs) [1]



Flight Plan Flexibility (FPF)

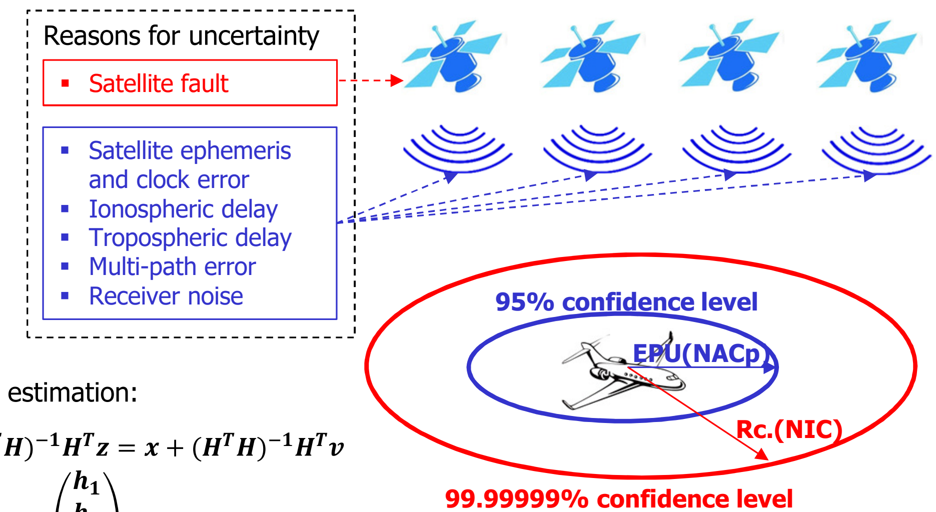
$$FPF = 1 - \frac{Area(FRV)}{Area(FRV) + Area(ARV)}$$

- An **FPF close to 0** indicates that most velocities among the aircraft's reachable velocities that will result in a LoS.
- An **FPF of 1** means that the aircraft may assume any reachable velocity and not incur any LoS.
- An **FPF of 0** means that a LoS is inevitable if no CD&R action is taken by any other aircraft in the system.

[1] S. Balasooriyan, "Multi-aircraft Conflict Resolution using Velocity Obstacles," Delft University of Technology, 2017.

Uncertainty management – uncertainty quantification of single ADS-B

- Reasons for positional uncertainty
  - Navigation satellite and onboard receiver derive the aircraft’s position
  - Normal and abnormal (fault) error induce the positional uncertainty



Position estimation:

$$\hat{x} = (H^T H)^{-1} H^T z = x + (H^T H)^{-1} H^T v$$

where $H = \begin{pmatrix} h_1 \\ h_2 \\ \dots \\ h_n \end{pmatrix}$, $v \sim N(0, \sigma)$

- Two levels of positional uncertainty broadcasted in ADS-B data

Level 1: Accuracy

- Position error at 95% confidence level only considering normal error
- In ADS-B data, this term is represented by **NACp** (Navigation Accuracy Category for position) from 0 to 11.
- The **EPU** (Estimated Position Uncertainty) is position error range denoted by NACp

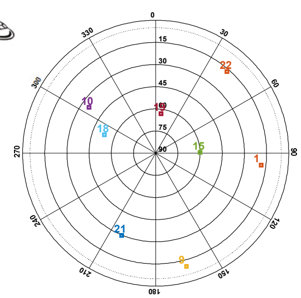
Level 2: Integrity

- Position error at 99.99999% confidence level considering navigation service failure cases
- In ADS-B, this term is represented by **NIC** (Navigation Integrity Category) from 0 to 11
- The **Rc.** (containment radius) is position error range denoted by NIC.

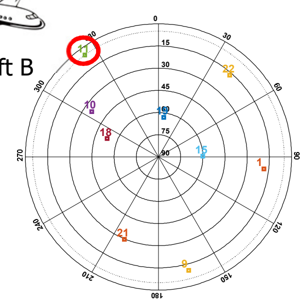
Uncertainty management – uncertainty quantification of a pair of aircraft

- The two aircrafts may view different satellite-set at a specific time
  - For example:

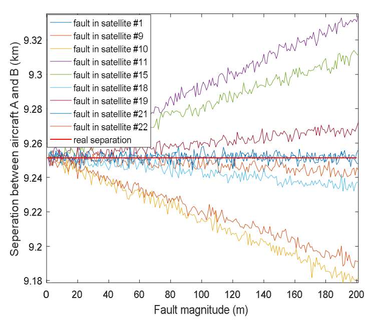
Aircraft A



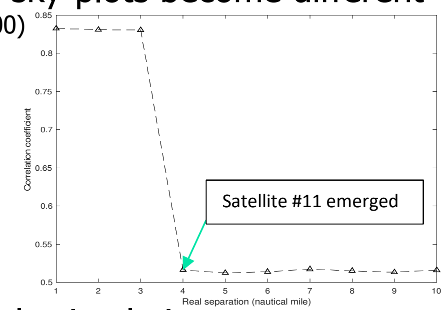
Aircraft B



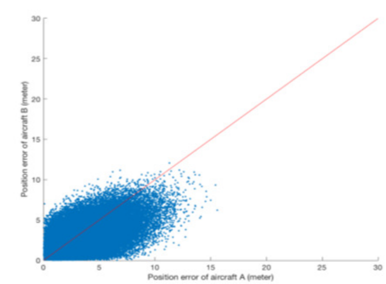
Sky-plots of the aircraft pair



- Position error correlation
  - The aircraft pair position error correlation is sharply reduced at real separation of 4nm when the sky-plots become different (time:03:33:00)



  - Monte Carlo simulation (real separation: 5nm)



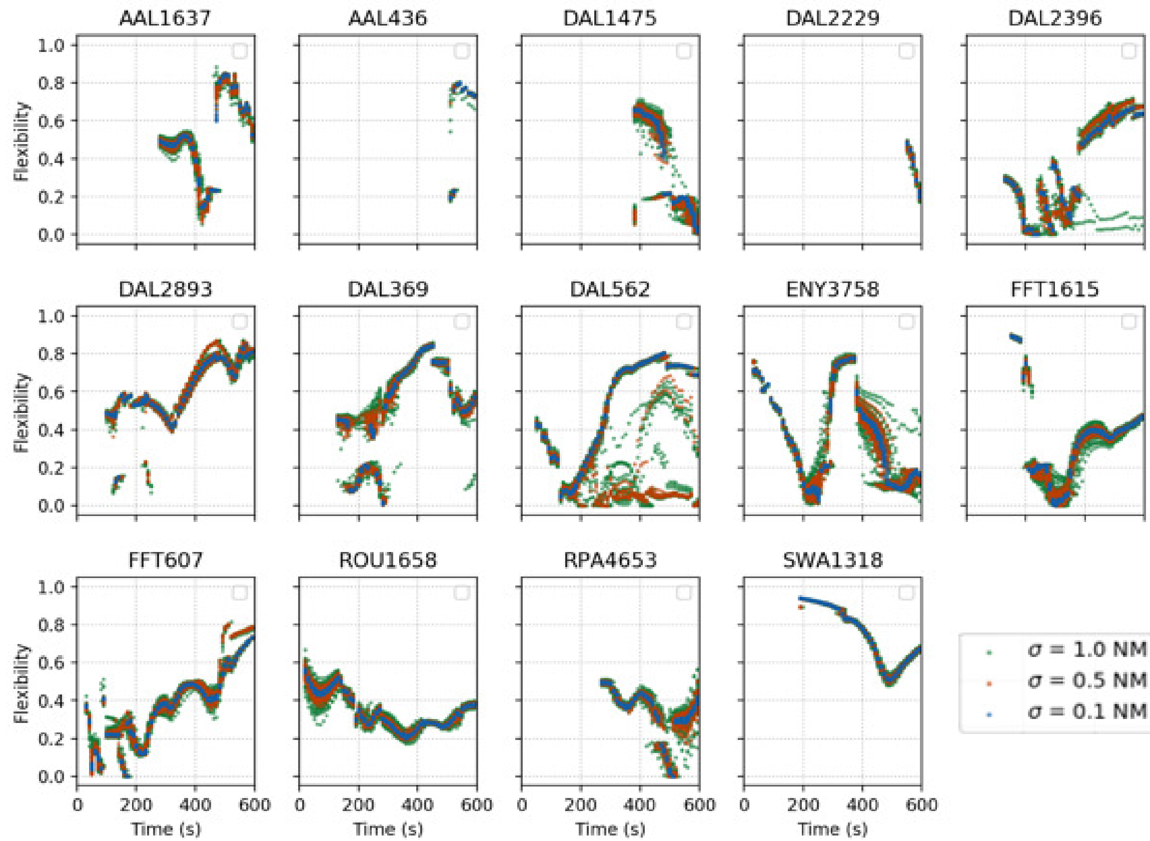
Uncertainty management – uncertainty propagation with simulation

Propagating ADS-B Uncertainty through BlueSky Simulations:

- BlueSky was connected with NESSUS® to propagate uncertainty with FPF as QoI
- 1000-point LHS was based on probability distributions of ADS-B signals for three Navigational Accuracy Categories for position (NACp) [2]

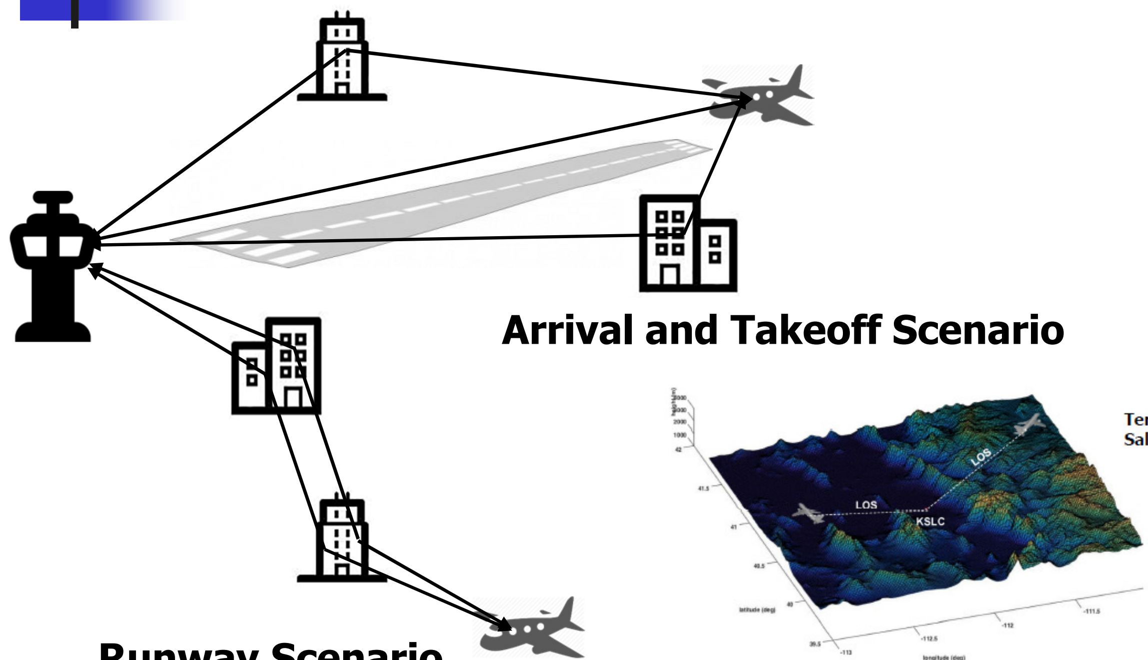
NACp Values and Corresponding Position Standard Deviation

NACp Value	Standard Deviation (NM)	Standard Deviation (degrees)
4	1.0	0.0016
5	0.5	0.008
7	0.1	0.016

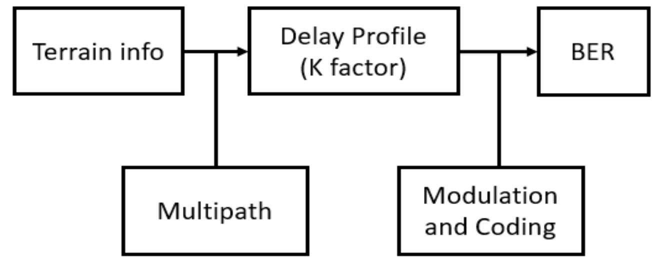


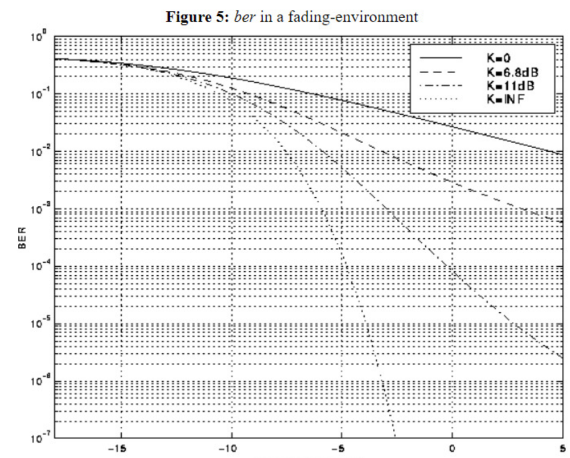
[2] Federal Aviation Administration (FAA) (2010) *Airworthiness Approval of Automatic Dependent Surveillance - Broadcast (ADS-B) Out Systems.* AC 20-165.

Uncertainty management – uncertainty from communications



Terrestrial objects such as mountains and buildings can cause multipath interference, different scenarios require different channel models.

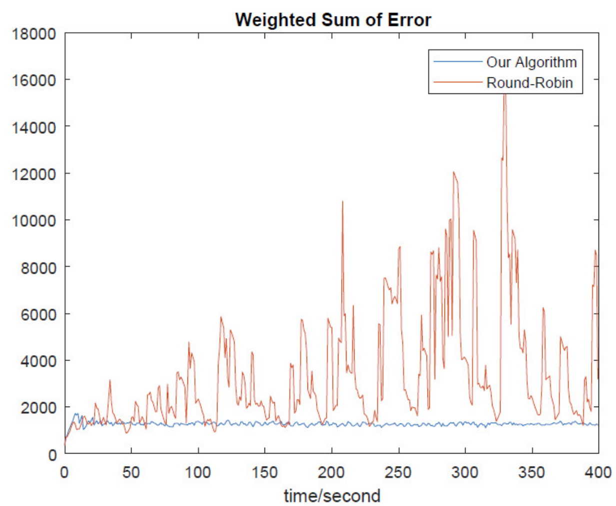


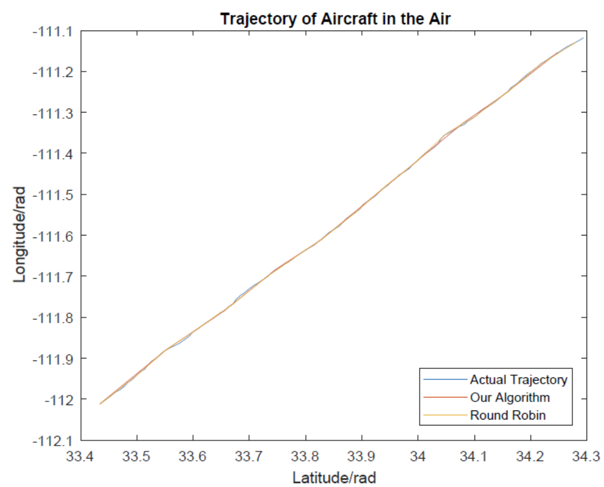


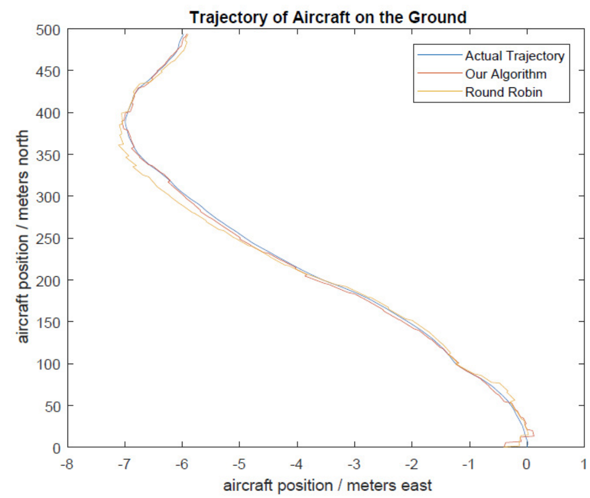
The relationship between SNR and BER under different K factor

Uncertainty management – uncertainty reduction via channel optimization

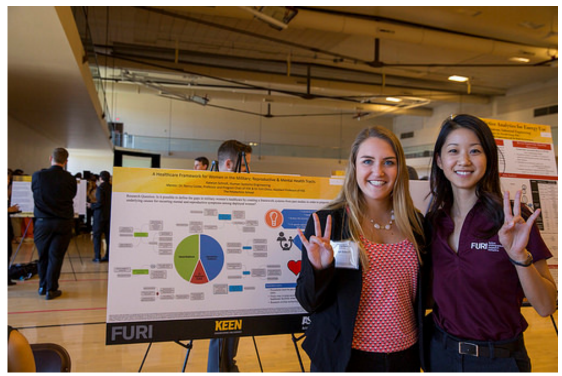
- Optimal scheduling of data transmissions to minimize the overall tracking error
- Significant reduction of uncertainty in the round-robin communication pattern
- Large impact of communication with terrain information for safety evaluation on the ground and near the airport







Educational activities and achievements

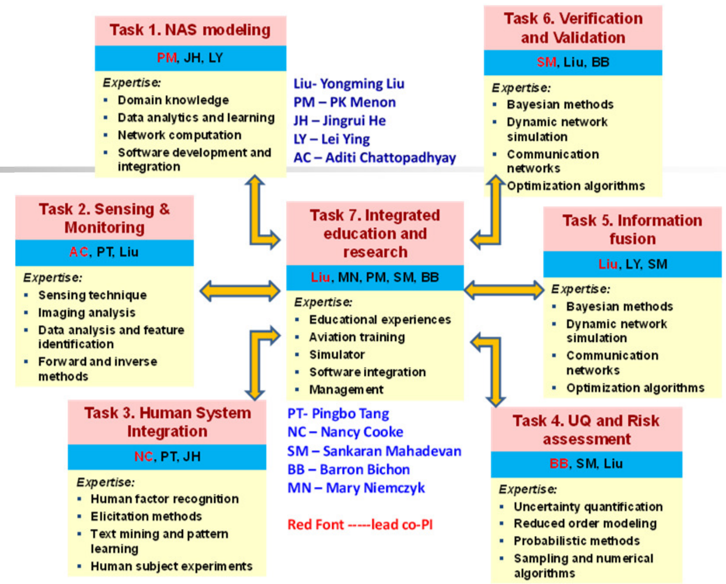


Fulton Undergraduate Research Initiative

Air Traffic Management Program

- 30+ students (PhD + MS + undergraduate students) from 7 majors (air traffic management, aerospace engineering, psychology, mechanical engineering, computer science, electrical engineering, and civil engineering)
- First MS graduate hired in ATM field
- First undergraduate design competition submitted for Airport Cooperative Research Program - SMART LINE UP AND WAIT SYSTEM FOR AIRPORT
- Fulton Undergraduate Research Initiative proposal – A $99 VORATS system (VOice Recognition for Air Traffic Simulators)
- Intergradation with ASU ATM program and PHX controller training program

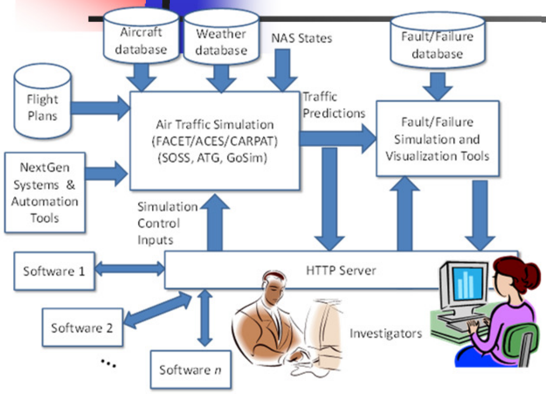
Project management - team



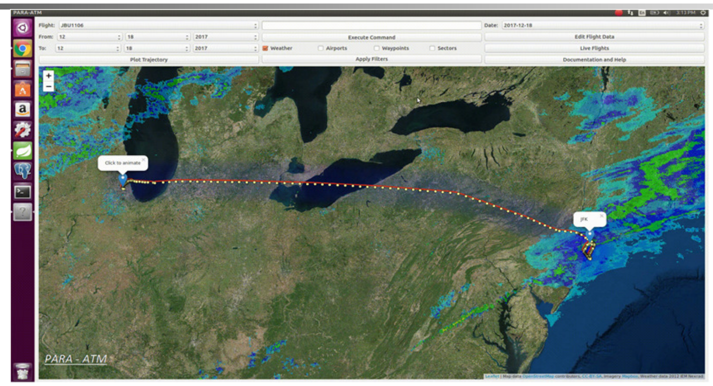
Team integration flow chart

- Diverse, multidisciplinary team that includes faculty in ASU's Ira A. Fulton Schools of Engineering and collaborators from Vanderbilt University, Southwest Research Institute and Optimal Synthesis Inc.
- Big data analysts, applied statisticians, image processors, psychologists, computer scientists, and aerospace engineers
- Expertise from information theory, applied statistics, data mining and analytics, risk management, airspace software systems, monitoring and imaging, and network science
- Smooth transition from academia basic research to applications of aerospace industry

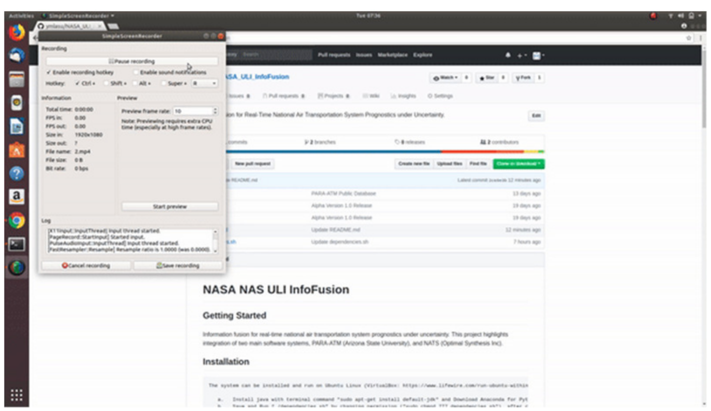
Research dissemination and community impact



NATS



PARA - ATM



Open source github sharing

- Development of simulation tools (NATS) to be used for future NextGen research
- Wide dissemination of research outcomes to aviation community
  - Prognostics Analysis and Reliability Assessment (PARA) - ATM
- Organize special sessions in conference to enhance the program impact
- External Advisory Board (EAB) that consists of various experts from industry, government agencies, and academia

External Advisory Board


Jeffrey Panhans,
Allegiant Air


Chid Apte,
IBM


Eric Haugse,
Boeing


Chuck Farrar ,
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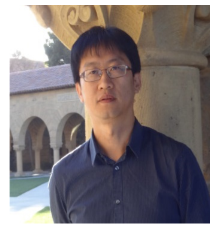
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Intel


Stephanie Cope,
Intel


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Raytheon


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UC Santa Cruz


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Pointivo


Lyle Hogg,
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Roger Mandeville ,
ATAC


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USRA


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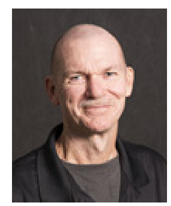
Verne Latham


Rob Hunt ,
FAA

- **External Advisory Board (EAB) – members from various different disciplines and industries**

EAB roles: 1) provide feedback and comments on the proposed research and research progress; 2) participate (in person or via telecom) in annual project meeting; 3) participate in regular progress teleconferences; 4) provide feedback and suggestions on future research directions to address important gaps in the community.

Conclusions and future work

- Fusing knowledge among multiple domains within the airspace system.
- Creating a multidisciplinary team of big data analysts, applied statistician, image processors, psychologists, computer scientists, and engineers.
- Improving air travel safety through complex human-cyber-physical system simulations using ultra-fast algorithms for real-time analysis.
- Developing extreme-scale, in-air and on-ground data sources to increase system reliability and risk management.
- Integrating multi-level education with K12 Education Outreach Program, Fulton Undergraduate Research Initiative, graduate student advising, and pilot training.
- Close collaboration with aviation industry enables future technology transfer.

Thanks!
Questions?

Acknowledgments

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